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Tracing The Spatial Patterns Of Innovation Determinants In Regional Economic Performance

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Abstract

This paper investigates factors of innovation and their role in regional economic performance for a sample of 261 EU NUTS 2 regions over 2009–2012. In our study, we identify regions with spillover as well as drain effects of innovation factors on economic performance. The spatial analysis indicates that both regional innovativeness and regional development, are strongly determined by the region's location and neighbourhood, with severe consequences for the Eastern and Central Europe.

We assessed the impact of innovation factors and their spatial counterparts on economic performance by spatial Durbin panel model. The model is designed to test the existence and strength of country-effect of innovativeness on the level of regional economic status. This allows for controlling the country-specific socio-economic factors, without reducing the number of degrees of freedom. Our model shows that regions benefit economically from their locational spillovers in terms of social capital. However, the decomposition of R&D expenditures revealed competition effect between internal R&D and external technology acquisition favouring in-house research over the outsourced ones.

Keywords: regional innovation, patterns of innovation, spatial spillover, common factors, spatial panel econometric model.

JEL Classification: O30, O33, C21, C23, R12.

1. Introduction

Recognition of patterns of innovations is essential for designing and implementing policies, which can help stimulate long-term output growth, improve productivity, as well as job creation. Recognising the innovation indicators is especially important at a regional level as it allows for the comparison of the local innovation performance and its influence on the local economic development. Such evidence is undoubtedly vital for proper policymaking. However,

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the evolution of new technologies and ideas is not merely confined to its administrative borders. That is, a company in a given location can benefit from research conducted at a nearby university, as well as projects developed by companies located in nearby regions. On the other hand, it would be more difficult for an individual firm to benefit from the innovative results of even the most dynamic region, should it be geographically distant. Nevertheless, each year the number of innovations carried out through collaborative networks is rising. (c.f. *Global Innovation Index 2016, as well as, 2017 and 2019 report*)

The Regional Innovation Scoreboard (RIS, 2016, 2017 and 2019) is an insightful analysis of the innovation performance in European regions. RIS 2016[1] is a study that considers the strengths and weaknesses of the regional innovation performance based on a number of selected indicators. These RIS indicators include variables on Research and Development (R&D) expenditure, patents, entrepreneurship, innovation collaboration and spread of innovative products.

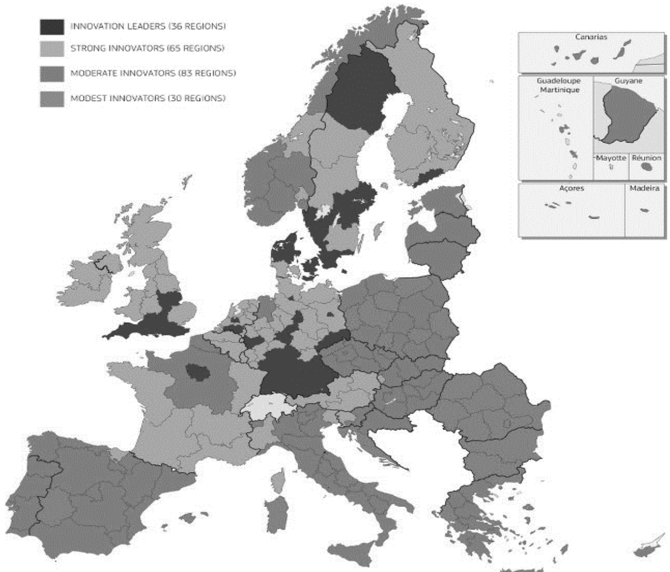
Figure 1 presents RIS 2016 with four performance groups ranging from Innovation Leaders to Modest Innovators. We have 36 regions of Regional Innovation Leaders, 65 regional Strong Innovators, 83 regional Moderate Innovators, and 30 regional Modest Innovators. Regional Innovation Leaders are located mainly in Sweden, Denmark, Finland, Germany, the Netherlands, UK, and Île de France in France. Strong Innovators are regions located in Germany, Austria, Belgium, Netherlands, UK, France, Norway, Italy, País Vasco in Spain, and Bratislavský kraj in Slovakia. Countries with moderate innovating regions are Portugal, Spain, Italy, Czech Republic, Slovakia, Hungary, Lithuania, Latvia, Estonia, Croatia, Greece, Poland, Weser-Emsin Germany, Bassin Parisien, Nord-Pas-de-Calais, and Départements d'outre-mer in France, and Vzhodna Slovenijain Slovenia. Finally, regional Modest Innovators are regions in Romania, Bulgaria, Poland, some Greek, Italian and Spanish islands, and Extremadura in Spain.

According to the RIS 2016 report, the regional performance corresponds to the European Innovation Scoreboard (EIS, 2016) country performance groups. As stated in the RIS report: "Almost all of the regional Innovation Leaders and Strong Innovators are located in the EIS Innovation Leader and Strong Innovator countries. Most of the regional Moderate and Modest Innovators are found in the EIS Moderate and Modest Innovator countries." Therefore, this might suggest the existence of a strong country-specific factor.

[1] Though there have been already published more recent RIS 2017 and 2019 reports, we refer to the 2016 study, as a more adequate to our data base.

Tracing the patterns of innovation is a valid topic, which has been widely studied in the literature for years. However, it is noteworthy that the regional aspect had not been studied much until the seminal work of Jaffe (1989). In his work, a version of the Griliches' (1979, pp. 92–116) Knowledge Production Function has been applied at a regional level. Since publication, this paper has served as an example for various studies such as the following (c.f. Anselin et al., 1997, pp. 422-448; Crescenzi et al., 2007, pp. 673-709; Cabrer Borrás & Serrano–Domingo, 2007, pp. 1357-1371; Gonçalves & Almeida, 2009, pp. 513-528). They all conclude that the proximity to highly innovative regions has a positive impact on their neighbours' development.

Figure1. Regional Innovation Scoreboard 2016



Source: European Innovation Scoreboard 2016

An intangible or knowledge-based capital has been widely recognised as an essential driver of innovation, growth, and competitiveness in the advanced economies (c.f. Corrado et al., 2009, pp. 661-685; Corrado et al., 2017). There are several works which stress a significant correlation between social capital and economic growth. All social structures, and in particular social networks, are essential factors for the economic outcome on account of the decrease in information costs and the reduction of information asymmetries (Granovetter, 2005, pp. 33–50). Caragliu and Nijkamp (2012, pp. 1363-1374) argue that insufficient levels of cognitive capital (that is social capital which accounts for cognitive skills like norms, customs, and psychological dispositions towards socio-economic interactions) can hinder European regions from fully benefitting from newly produced knowledge.

This paper aims to identify knowledge-based innovation factors that determine regional economic performance and to determine for which factors the complementary or the competitive effect can be found. Moreover, as innovation is expected to occur in (regional) spatial patterns, we aim to test whether there are any common, national-specific factors. In order to reach this goal, first, we aim to identify regions and their clusters sharing a similar level of innovativeness and their relation to regional development using spatial statistics. Then, as the main part of our analysis, we introduce an econometric model to verify the innovation-based determinants of regional growth.

The rest of the paper is structured as follows. Section 2 presents the description of variables and the data used in the empirical part of the analysis. Section 3 provides a brief theoretical background of uni- and bivariate Moran's *I* statistics as well as a presentation of the Durbin's Spatial Autoregressive Panel Model with spatial fixed effects used in the empirical part of the paper. The results from the analysis and the discussion are presented in Section 4. Section 5 offers a summary and some closing remarks.

2. Determinants and data

In our study, in line with the RIS report, we select innovative determinants of regional economic performance, namely high-tech employment, and patent applications, representing social capital and R&D investments. Data used in the study is taken from the Eurostat Regional Database. Some missing data were interpolated from past trends and the data derived from NUTS 1 and NUTS 0 level. In this research, we considered 261 EU regions from 27 countries from 2009 to 2012. Moreover, for the description of the spatial structure for the EU regions, we used the three nearest neighbours (3nn) spatial weights matrix **W** (c.f. Anselien, 1998).

While the data on tertiary education gives valuable information on the future prospective highly-qualified labour force in Europe, the indicator of employment in technology and knowledge-intensive sectors provides the exact knowledge on the proportion of people actually working in technological and knowledge-intensive fields. Therefore, we used specifically this indicator as one of the critical factors of innovations. In our study, the employment in technology and knowledge-intensive sectors (H) refers to as the share of employees in technology and knowledge-intensive sectors of the total number of the economically active population. Human capital in nearby locations is described by its spatial lag (**W**H).

In our study, we use patent applications to the European Patent Office (EPO), as the other important element of social capital. However, we are aware that the intensity of patenting may vary depending on the sector or the characteristics of companies. Moreover, not all inventions are patented, patent values are different, and finally, not all patents lead to significant technological improvements. However, since all EU countries have national patent systems, and the data covers most of the technological fields, patents are often used as indicators of innovation. In this work, patents are represented by the patent applications to EPO by priority year per million of active population (EPO). Patent applications in neighbouring regions are defined by its spatial lag (**W**EPO).

Research and experimental development comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications. (Frascati, 2002) The intensity of research and experimental development (research and experimental development expenditures as a percentage of GDP) is an indicator of high political importance at the EU, national and regional levels. Therefore, we use R&D expenditures as one of the critical indicators of innovations. In our study, the variable R&Dexp represents the total intramural R&D expenditures, approximated by the gross domestic expenditure on R&D (GRED) in PPS (constant prices 2000) per economically active population. R&D expenditures in neighbouring regions are represented by its spatial lag (**W**R&Dexp).

As a measure of regional performance, we take local gross domestic product per economically active population (expressed in thousands of people at the age of 15 and over) which has been converted into a common scale using purchasing power standard (PPS, in millions), and expressed in constant prices from the year 2000. GDP in bordering regions is described by its spatial lag (**W**GDP).

The distributions of variables used in the study in the last year of analysis - 2012 are presented in Table 2. All the variables are expressed in logarithms. Table 1 offers the descriptive statistics of those.

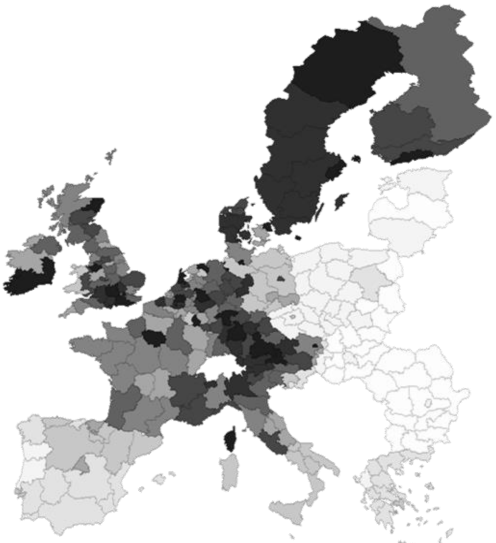
Table 1. Descriptive statistics of variables used in the analysis

Variable	Description	Mean	σ	Min	Max
GDP	Regional GDP in Millions (PPS, cs 2000) per thousand of economically active population	43.9	22.2	3.8	178.6
R&Dexp	Total intramural R&D expenditure (GERD)(PPS, cs 2000) per economically active population	764.3	782.7	11.3	6 697.8
H	Employment in technology and knowledge-intensive sectors per economically active population	0.9	0.1	0.6	1.2
EPO	Patent applications to the EPO by priority year per million of economically active population	199.0	231.2	0.0	1399.2

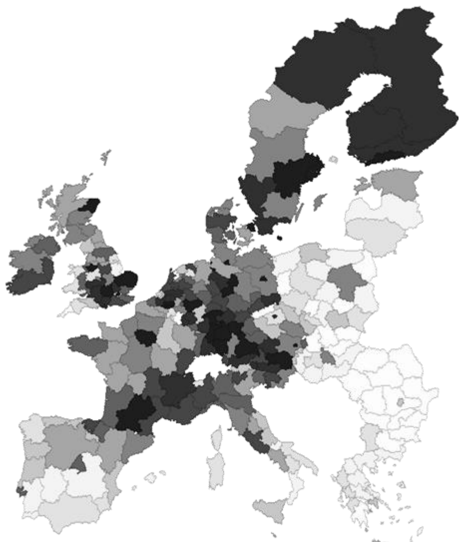
Source: own study based on research.

Table 2. Variables used in the analysis, year 2012

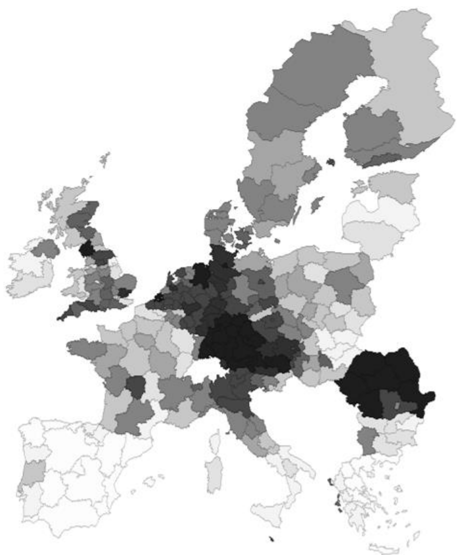
Regional Gross Domestic Product
(PPS, constant prices 2000)



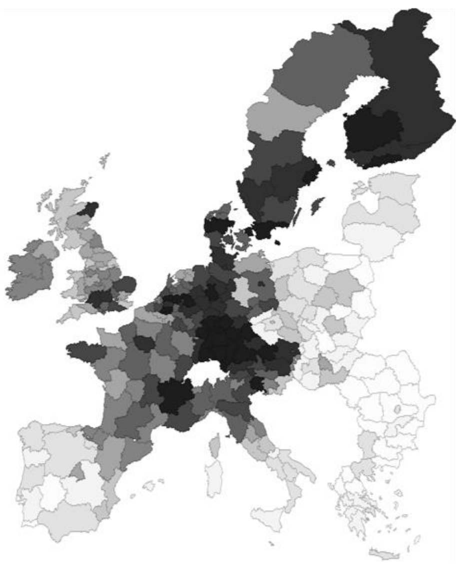
Total intramural R&D expenditure
(PPS, constant prices 2000)



Employment in technology and knowledge-intensive sectors



Patent applications to the EPO



Source: own study based on research. (Shading of each variable is a quantile (10); the higher the value, the darker the colour)

3. Theoretical background

One of the most basic tools of spatial analysis is Moran's I statistic (Moran, 1948, pp. 243-251; Cliff and Ord, 1981). We distinguish two basic types of Moran's I statistics: local and global. As a measure of local spatial association, the local Moran's I_i indicates if the i-th spatial object is surrounded by other spatial objects with similar (positive spatial autocorrelation) or significantly different (negative spatial autocorrelation) values of the variable in question

$$I_i = \frac{(x_i-\bar{x})}{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2}\sum_{j=1}^{N} w_{ij}\left(x_j - \bar{x}\right), \tag{1}$$

where x_i represents the variable in question, $\bar{x}$ its mean and w_{ij} representing elements of spatial weight matrix **W**. On the other hand, the global Moran's *I* statistic is a more general measure of regional association as it expresses the likeness of all spatial objects as a mean of the local Moran's I_i statistics

$$I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2}. \tag{2}$$

While both local and global Moran's *I* aim to measure the similarities and dissimilarities between one spatial variable, the bivariate local Moran's *I* explains the spatial pattern formed by two different variables. That is, it measures spatial autocorrelation between variable x and another variable (y) in nearby areas

$$I_i = \frac{(x_i-\bar{x})}{\frac{1}{N}\sum_{j=1}^{N}\left(x_j-\bar{x}\right)^2}\sum_{j=1}^{N} w_{ij}\left(y_j - \bar{y}\right), \tag{3}$$

with analogous notation.

The generalisation of the cross-sectional spatial autoregressive (SAR) model (Ord 1975, pp. 120-127; Kelejian and Prucha 1998, pp. 99-121, and 2010, pp. 53-67) to the panel setting has been very popular in literature. In addition to the spatial lag of the dependent variable, a spatial lag of independent variables can be included in the regression, which leads to the so-called spatial Durbin model. (see, e.g., LeSage and Pace, 2009) The identification of the spatial Durbin panel model concerns the effect of the spatial lags of the dependent variable in the presence of spatial time lags and exogenous spatial variables (Anselin et al., 2008, pp. 627–662 and Elhorst, 2014). This approach is a beneficial and flexible instrument in the process of specification of the econometric model, as it can incorporate spatial lags of the exogenous variables on the right-hand side of the equation. In order to introduce some notation used in the study, we present a theoretical formula for the spatial Durbin panel model with spatial fixed effects

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\vartheta},\ \ \boldsymbol{\vartheta} = [\mu_i + \varepsilon_{it}]_{it}, \varepsilon_{it} \sim N(0,\sigma^2), \tag{4}$$

where **y** (NT×1) is a vector of observations on the dependent variable and **X** (NT×K) represents matrix of observations on K independent variables, **W** is a pre-defined spatial weight matrix representing spatial structure of observations, **WX** is a matrix of spatial lags of the independent variables, **Wy** spatially lagged vector dependent variable, ρ is a spatial coefficient. Parameter

ε_{it} is a vector of random errors, and μ_i represent spatial fixed effects, where $1 \leq i \leq$ N and $1 \leq t \leq$ T.

In order to account for the role of country-specific effect, among others, we tested the spatial Durbin panel model with spatial group effects. In spatial group effects model instead of spatial fixed effects term μ_i, we introduce the term $\varphi_{group(i)}$, $1 \leq group(i) \leq$ K, $1 \leq i \leq$ N, where K represents number of groups (Olejnik and Olejnik, 2020)

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\vartheta}, \ \boldsymbol{\vartheta} = \left[\varphi_{group(i)} + \varepsilon_{it}\right]_{it}, \varepsilon_{it} \sim N(0, \sigma^2), \quad (5)$$

Notice that the spatial group fixed effects can be tested using two-step procedure based on the augmented CD-test (c.f. Elhorst *et al.*, 2018, Olejnik and Olejnik, 2020).

4. Results and discussion

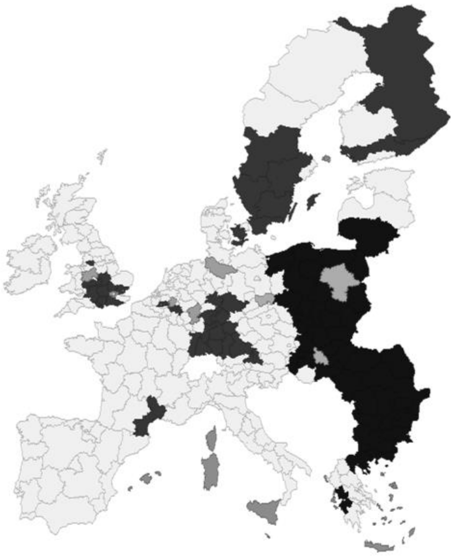
We start our analysis by focusing on individual regions and identification of clusters sharing a similar level of innovativeness using univariate spatial statistics. This enables the identification of spillover effects for individual regions via hot and cold spots as well as drain effects pinpointed by mixed clusters (hot-cold or cold-hot). In the second step, we confront the chosen innovation factors with the level of regional development by employing the bivariate Moran's measure to highlight individual regions for which high/low levels of innovation factors in nearby locations coincide with high/low GDP.

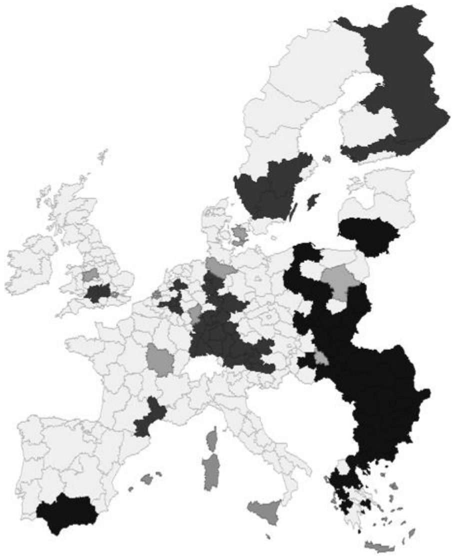
Finally, we expand the spectrum of the analysis to search for more general mechanisms and regularities in the determinants of innovation factors. By incorporating a multivariable causality spatial Durbin panel model of economic performance determined by selected indicators of regional innovativeness and their spatial counterparts, we aim to assess the statistical significance of each factor. Moreover, the model is designed to test the existence and strength of country-effect of innovativeness on the level of regional economic status.

Below, local univariate and bivariate have been performed for 250 regions (as 11 regions have been definite as neighbour-less). Table 3 and 4 report results from a univariate LISA analysis for the first (2009) and the final year of study (2012). Table 5 and 6 provide the results from bivariate LISA (2009 and 2012, respectively).

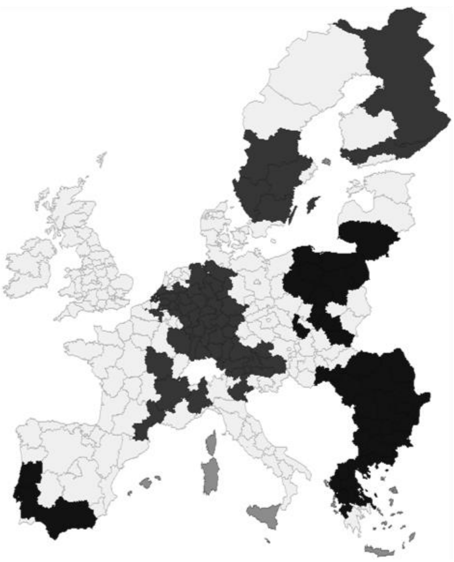
Table 3. Univariate Local Moran's *I* for R&D and EPO, 2009 and 2012

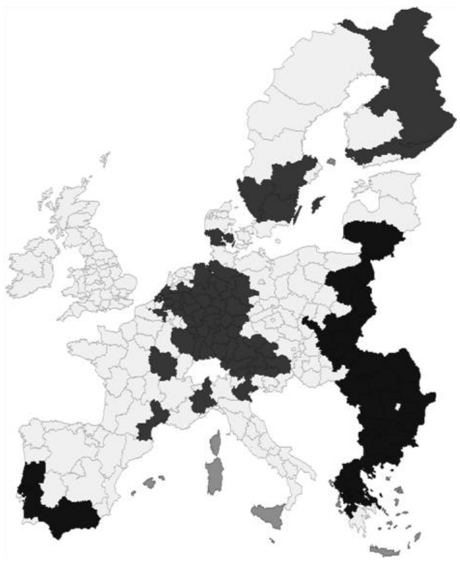
R&D, 2009, Moran's *I*=0.61 | *R&D,* 2012, Moran's *I*=0.6



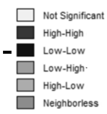


EPO, 2009, Moran's *I*=0.59 | *EPO*, 2012, Moran's *I*=0.42





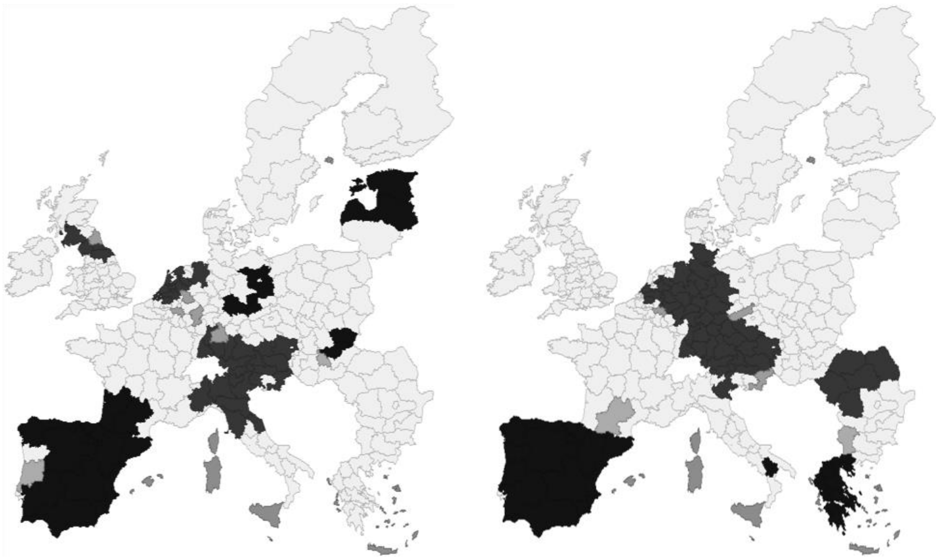
Colour legend for statistically significant outcomes -



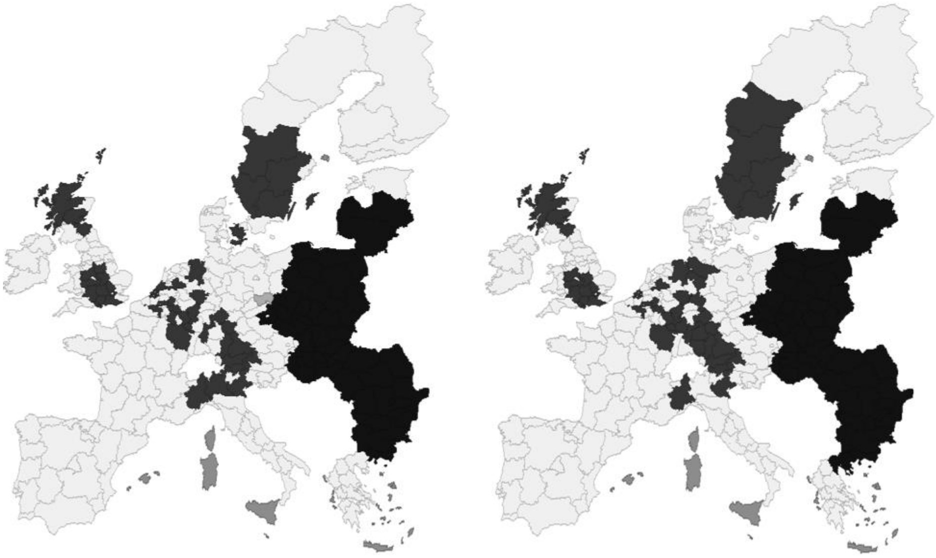
Source: own study based on research.

Table 4. Univariate Local Moran's *I* for H and GDP, 2009 and 2012

H, 2009, Moran's *I*=0.47 | *H,* 2012, Moran's *I*=0.66



GDP, 2009, Moran's *I*=0.86 *GDP*, 2012, Moran's *I*=0.85

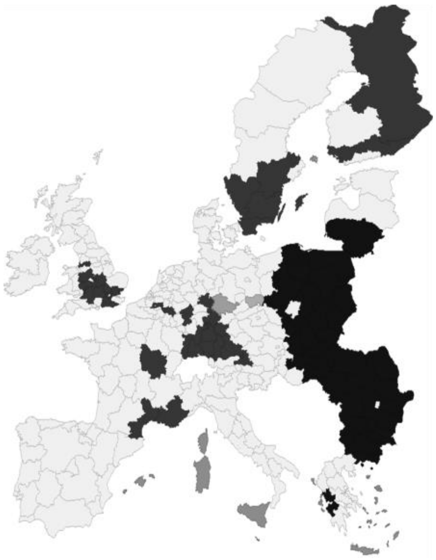


Colour legend for statistically significant outcomes -

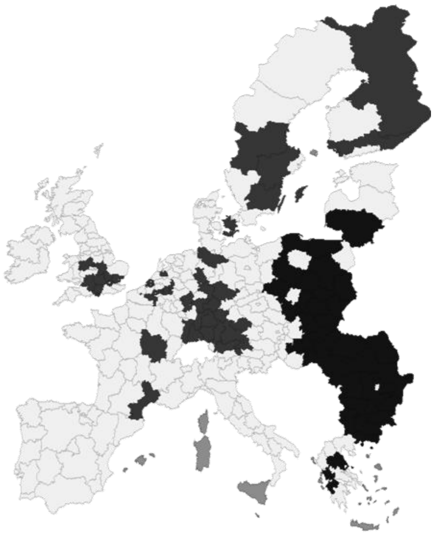
Source: own study based on research.

Table 5. Bivariate Local Moran's *I*, for GDP with **W***R&D* and **W***EPO*

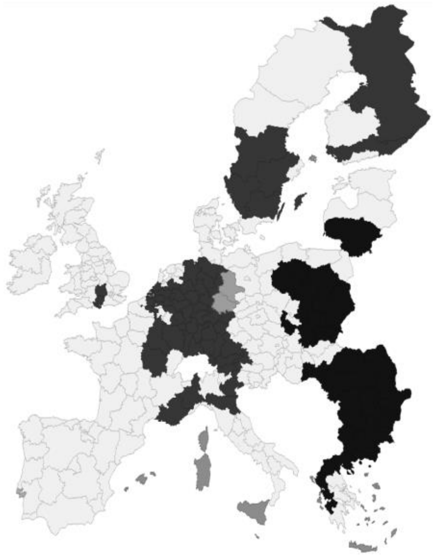
GDP – **W***R&D*, 2009, Moran's *I*=0.70



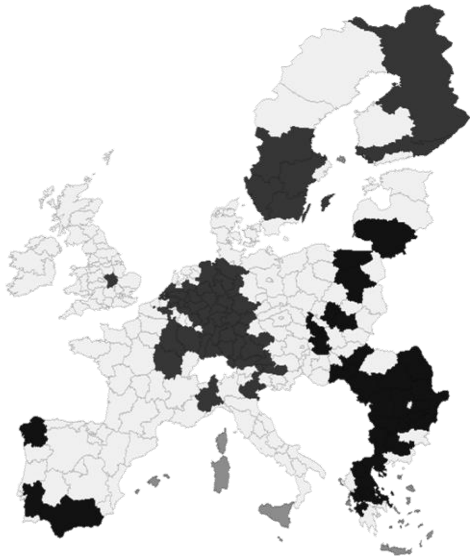
GDP – **W***R&D*, 2012, Moran's *I*=0.70



GDP – **W***EPO*, 2009, Moran's *I*=0.69

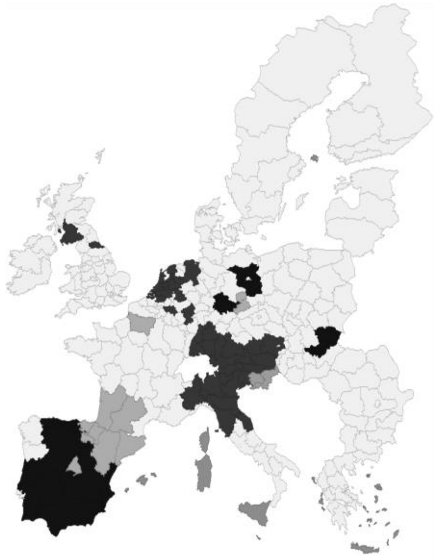
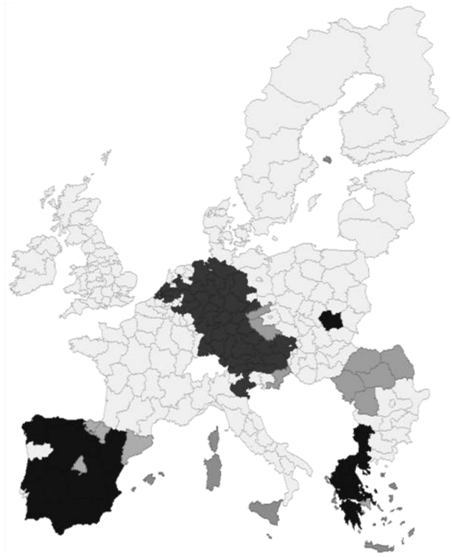


GDP – **W***EPO*, 2012, Moran's *I*=0.54



Source: own study based on research.

Table 6. Bivariate Local Moran's *I*, for GDP with $\mathbf{W}\boldsymbol{H}$

GDP – **W***H*, 2009, Moran's *I*=0.17	*GDP* – **W***H*, 2012, Moran's *I*=0.2
	

Source: own study based on research.

The spatial autocorrelation for the total intramural R&D expenditures is high, with Moran's *I*=0.6. From the maps, we can observe 33 clusters of regions with high R&D expenses surrounded by regions also with high expenditures (high-high, hot-spots) in Finland, Southern Sweden, Germany, a few regions in the UK, Alsace and Tarn in France, Liège in Belgium, Luxembourg, Sjælland in Denmark, and Salzburg in Austria. On the other hand, we have 41 low-low clusters (cold-spots) of regions with low R&D expenses bordering areas with similarly low expenditures, mainly in the Eastern part of the EU. The spatial pattern seems to be similar for 2009 and 2012, except for Andalusia in Spain and Greece where new cold-spots emerged, the UK where a few hot-spots disappeared, and some regions of Poland where a few cold-spots disappeared, and some new hot-spots appeared in Germany.

The spatial autocorrelation for patent applications to the EPO by priority year per million of active population is high, with Moran's *I*=0.6, in 2009 and *I*=0.4 in 2012. From the maps, in Table 3, one can observe clusters of regions with a high number of patent applications surrounded by regions also with a high number of patent applications (high-high cluster, hot-spots) in Finland, Southern Sweden, Germany, France (Lorraine, Alsace, and Burgundy), Belgium (Namur, Hainaut, Flemish Brabant, Antwerp, Limburg, Liège), the Netherlands (Gelderland, South Holland, North Brabant, and Limburg), Southern Denmark, Piemonte and Veneto in Italy, and Austria. Cold-spots are located mainly in the Eastern part of the EU, Portugal, and southern Spain.

The spatial autocorrelation of employment in technology and knowledge-intensive sectors per economically active population is high, with Moran's I=0.5, in 2009 and I=0.7 in 2012. In contrast to the earlier indicators, the difference between the year 2009 and 2012 is noticeable. From the maps (Table 4) we can observe clusters of regions with high employment surrounded by regions with similarly high employment (high-high) in Namur, Hainaut, Flemish Brabant, Antwerp, Limburg, Liège in Belgium, Eastern Netherlands and North Brabant in the Netherlands. The Northern part of Italy, South West Scotland, North Yorkshire, Tees Valley, and Durham in the UK were in high-high clusters only in 2009. On the other hand, one can observe an additional hot-spot in Romania, some new hot-spots in Germany, Austria and Benelux. At the same time, we have disappearing cold-spots in Latvia, Estonia and Germany, and even a change from cold- to hot-spot in Thüringen (Germany) over time. Overall, by 2012 the number of hot-spots had increased from 36 to 52, and the number of cold-spots had remained stable; however, it had concentrated mainly in the Iberian Peninsula and Greece.

The spatial autocorrelation of GDP per active population is very high (Moran's I=0.86, in 2009 and I=0.85 in 2012) with a very similar spatial pattern for both years. From the maps (Table 4) we can observe hot-spots mainly in Southern Sweden, Scotland, Midlands and the South East of the UK, Northern Italy, Austria, some regions in Germany, Belgium, and the Netherlands. Regions with a low GDP surrounded by regions with a similar level of GDP (low-low) cluster in the Eastern part of the EU.

The spatial clustering of individual indicators of innovativeness alines with most of RIS conclusions. Moreover, we do observe the spillover effect from Innovation Leaders to Followers.

For R&D expenditures and patents, we see that South and East Middle Sweden, as well as Stockholm, are indeed Innovation Leaders and the spillover effect can be seen for Småland and the islands. Similarly, in Finland, spillover occurs from Innovation Leaders (Lapland and Helsinki-Uusimaa) to eastern regions, which are the Innovation Followers. In the United Kingdom, Innovation Followers like Gloucestershire, Wiltshire, and the Bristol/Bath area are mainly benefitting from Innovation Leaders: Berkshire, Buckinghamshire, and Oxfordshire and Surrey, East and West Sussex.

In the case of employment in technology and knowledge-intensive sectors, the spatial clustering analysis only partially coincides with RIS innovators classification. The only spilling-over from

Innovation Leaders can be seen in Germany, the Netherlands and Austria. Additionally, human capital is spilling-over from Moderate Innovators in northern Italy.

It is noteworthy, in our analysis, we do not observe, any significant impact of Moderate Innovators on neighbouring regions. This is especially visible in the eastern part of the EU.

Table 5 and 6 present results from the bivariate LISA analysis for the years 2009 and 2012 for all three innovation factors with a regional GDP.

The spatial association between the regional GDP and the total intramural R&D expenditures in neighbouring regions is high, with Moran's I=0.7. From the map, we can observe clusters of regions with a high GDP surrounded by regions with high R&D expenditures in Finland, Sweden, Germany, the UK, France, the Netherlands, Belgium, Denmark, and Austria. On the other hand, we also have clusters of regions with a low GDP border as well as low R&D expenditures in the Eastern part of the EU.

Additionally, the spatial association between the regional GDP and patent applications to EPO in bordering regions is high, with Moran's I=0.69 in 2009, and with I=0.54 in 2012. Moreover, local clusters of regions with a high GDP surrounded by regions with a high number of patent applications are visible in regions of Finland, Sweden, Germany, France, the Netherlands, Belgium, Italy, Austria, the UK. We also have clusters of regions with low GDP adjacent to regions with a low number of patent applications in Greece, Bulgaria, Romania, Poland, Lithuania, Hungary, and additionally Portugal and Spain in 2012.

From Table 6 it is distinct that the global spatial autocorrelation between the regional GDP and employment in professional sectors in neighbouring regions is low, with Moran's I=0.2. However, one can observe local clusters of regions with a high GDP surrounded by regions with high employment in R&D in Germany, the Netherlands, Belgium, Austria. Additionally, there are also clusters of regions with a low GDP bordering low R&D employment in Portugal, Spain, and in 2012, in Greece and Malopolskie in Poland.

In the central part of our analysis, in order to investigate whether the influence of innovation factors in neighbouring regions stimulate economic performance within the region, we performed a spatial Durbin panel model with random and fixed effects ($\varphi_{group(i)} + \varepsilon_{it}$). To this end, we consider the following specification

$$GDP_{it} = \rho \mathbf{W} GDP_{it} + \gamma_1 \mathbf{W} H_{it} + \gamma_2 \mathbf{W} EPO_{it} + \gamma_3 \mathbf{W} R\&Dexp_{it} + \beta_1 H_{it} + \beta_2 EPO_{it} + \\ + \beta_3\ R\&Dexp_{it} + \varphi_{group(i)} + \varepsilon_{it}, \tag{5}$$

where GDP_{it} represents GDP in the *i*-th region and the year *t* (PPS; constant prices of 2000), H_{it} – employment in technology and knowledge-intensive sectors per economically active population in the *i*-th region and the year *t*, EPO_{it} – patent applications to the EPO by priority year per million of active population in the *i*-th region and the year *t*, $R\&Dexp_{it}$ - total intramural R&D expenditure (GERD) (PPS; constant prices of 2000) per economically active population, $\mathbf{W}GDP_{it}$ indicates the mean of GDP in neighbouring (in the sense of 3nn weight matrix) regions in the year *t*. The variables $\mathbf{W}H_{it}$, $\mathbf{W}EPO_{it}$, $\mathbf{W}R\&Dexp_{it}$ are defined analogously.

The preliminary results from ML procedures indicated that the level of human capital, as well as patent applications within the given region, does not have a significant and direct impact on economic performance. Their spatial counterparts, however, do.

The final model takes the following form

$$GDP_{it} = \rho\mathbf{W}GDP_{it} + \gamma_1 \mathbf{W}H_{it} + \gamma_2\mathbf{W}EPO_{it} + \gamma_3\mathbf{W}R\&Dexp_{it} + +\beta_3 R\&Dexp_{it} + \varphi_{country(i)} + \varepsilon_{it}. \tag{6}$$

Parameter $\varphi_{country(i)}$ represents spatial effects common for each country (country-specific fixed effect), where $1 \leq country(i) \leq 27, 1 \leq i \leq 261$, as the sample consists of 261 regions for 27 countries, and therefore we introduce 27 spatial-fixed effects into the model. In our study, we considered both country-specific and regional fixed effect specifications. However, we have found that the incorporation of the country-specific fixed effects considerably improved goodness of fit of the model. At the same time, farther extension to the usual regional fixed effect specification provided virtually no improvement. This implies that employing the country-specific effects allowed for controlling the country-specific socio-economic factors, without reducing the number of degrees of freedom too much.

Table 8. Spatial Durbin panel model with country-fixed effects

variable	estimates	var	t-value	p-value
Rho	0.146	0.036	4.071	<0.00001
W *H*	0.817	0.166	4.918	<0.00001
W *EPO*	0.021	0.009	2.263	0.023657
W *R&D exp.*	-0.039	0.015	2.604	0.009203
R&D exp.	0.193	0.007	26.258	<0.00001
R^2_pseudo with FE	0.94			
N	261			
T	4			

Source: own study based on research.

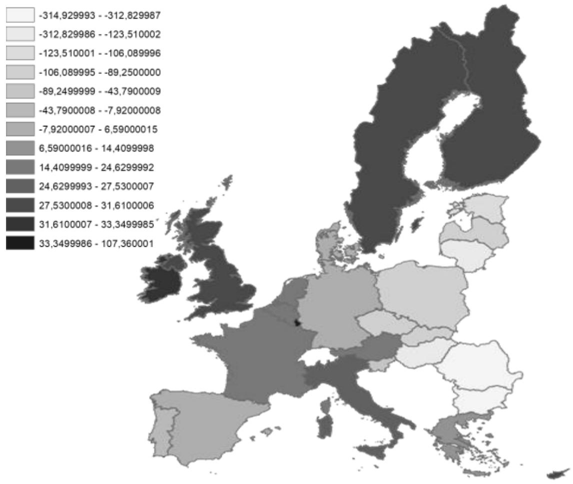
Table 8 presents the estimation results. All coefficients associated with the explanatory variables of the model appear significant at the 5% confidence, which suggests that the chosen set of innovation factors significantly explain economic performance in the EU regions. Most importantly, the significance of the spatial coefficient and spatial lags of explanatory variables confirms the assumed complex structure of the interregional interactions of innovation factors. Furthermore, let us notice that the value of goodness of fit (0.94) suggests a good adjustment of the model to the empirical data.

From the outcomes, we conclude that the inclusion of spatially weighted human capital in the set of innovation determinants of economic performance proved to be valid. Essentially, the employment in technology and knowledge-intensive sectors in nearby regions has a positive impact on regional income. Also, the empirical outcomes show that patent applications to EPO in neighbouring locations statistically have a significant effect on the economic performance within the region. Therefore, we conclude that regions benefit economically from their locational spillovers in terms of social capital, as suggested by the spatial patterns described by uni- and bivariate analysis and confirming the complementary effect of the above innovation factors.

In general, a high level of innovation factors in surrounding locations stimulate economic performance within the region. Interestingly, this does not apply, however, to the expenditures on research and development, where we do not see substitution or complementarity between internal R&D and external technology acquisition.

It should be noted that in the results of bivariate LISA analysis, strong and positive correlations between GDP and **W**R&D have been found. However, the econometric model, in which decomposition of R&D expenditures have been applied, revealed that the actual impact on economic performance from nearby regions is, though highly significant, negative. This means that the more substantial expenditures in neighbouring regions, the more impoverished the region, *ceteris paribus*. So, our results suggest no regional complementarities for R&D investments. At the same time, a positive and significant coefficient associated with expenditures on in-house research indicates that the more substantial R&D expenditures within the region, the more prosperous region. From that, one can conclude that our model reveals regional competition effect of the R&D expenditures, favouring in-house research over the outsourced ones. This could be caused by the issue of limited resources, where possible, higher funding in one region comes at the expense of other regions, in result, inhibiting their economic development.

Figure 2. Country fixed effects for regional economic performance for innovation determinants in UE



Source: own study based on research.

The final specification of the econometric model confirmed that country-specific effects surpass the individual regional effect and common constant value for all locations. This means that while in each region the GDP is influenced by its innovativeness as well as the innovativeness of bordering regions, all regions within a single country have a mutual (common) time-constant baseline or starting-point level of regional development. This common factor reveals the contribution of innovation factors in wealth creation.

5. Conclusions

For the analysis of individual regions, we conclude that in EU innovation factors appear in polarised structure with agglomerations in Central EU with Sweden and Finland versus Eastern EU and the Iberian Peninsula. A similar spatial pattern is also reflected in the RIS report, for Innovation Leaders and Strong Innovators versus Moderate and Modest Innovators.

In the case of the Iberian Peninsula, one can observe extremely low employment in science and technology, which has been decreasing over time. This is probably caused by the largest share of the population with the lowest level of education in the EU. (Educational attainment statistics) This, together with a very low level of expenditures on research and development, correspond with declining development in Spain and Portugal. This disturbing trend may have severe consequences for the economy in this part of the EU. It should also be noted, that while Poland, together with some neighbouring states, like Lithuania, the Czech Republic, and Slovakia are considered as less developed countries in the EU and rather moderate to modest innovators, their expenditures for research and development and patent applications are increasing over time. This is also reflected in the high incline of GDP in this part of the EU.

This may suggest that the awareness of innovativeness and its influence on regional development has risen in the region. Lastly, the performance of regional innovation appears to be relatively stable throughout the period of analysis.

This paper aimed to trace knowledge-based innovation factors that determine regional economic performance. Our results validate the assumed complexed structure of the interregional interactions of innovation factors. We established that the complementary effect occurs for social capital, namely human capital and patent applications with strong spillover effects. In the case of research and development expenditures, however, our analysis revealed both regional clustering of similarly high or low R&D expenses in large parts of Europe as well as a regional competition effect, which indicates preferring internal research programs over the external technology acquisition. This result of a spatial panel model challenges the cooperation paradigm in the innovation process. Moreover, the spatial analysis indicates that regional innovativeness and regional development are strongly determined by the region's location and neighbourhood. This constitutes an unfair and unalterable disadvantage to Eastern and Central Europe.

In the analysis, we have specified and estimated a country fixed effects which represent spatial effects common for each country. They appear to be significant and highly diverse, therefore, essential from the viewpoint of the analysed innovation-determined economic performance process. This factor might be associated with some socio-economic, legal, administrative, or cultural aspects, like the education system or a willingness to take risk and reveals the contribution of innovation factors to wealth creation.

Our research reveals that there are spatial patterns in innovation factors, and therefore, innovation is not merely confined to its administrative borders, despite the presence of country-specific factors. What is more, there is considerable diversity in the performances of regional innovation indicators.

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